Developing Chatbots in Higher Education:  
A Case Study of Academic Program Chatbot in Thailand

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Abstract

Millennials prefer text messaging over phone calls as it is convenient and easy to use. Chatbots, where the primary mode of communication is texting, could offer self-service options, handle simple tasks, and provide 24/7 availability for customers. Chatbots have been used in the education sector in different functions. Many colleges are using a chatbot to respond to common enrolling questions. This paper uses one example of an academic program Facebook Page to illustrate how chatbot implementation could benefit. The end-to-end development process of this chatbot using Google Dialogflow as NLU platform and Facebook Messenger as the platform interface is also discussed. A total of 807 sentences from 125 users were collected from the chat logs as a representative sample which can develop into 33 intents. The proposed chatbot achieves satisfying precision, recall, and F1-score reported as 0.984, 0.884, and 0.897, respectively. The implementation of chatbots also solved the problems faced by page administrators and end-user.

Keywords: Artificial intelligence, Chatbot, Conversational agent, Chatbot platform, Dialogflow

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การพัฒนาแชทบอทสำหรับใช้ในระดับอุดมศึกษา
กรณีศึกษาแชทบอทของสาขาวิชาหนึ่งในประเทศไทย

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Abstract

ในปัจจุบันประชากรกลุ่มมิลเลนเนียล (Millennials) เลือกที่จะติดต่อผ่านการส่งข้อความมากกว่าการสนทนาทางโทรศัพท์ เนื่องจากมีความสะดวกกว่าและสามารถทำได้ง่ายกว่า แชทบอท (Chatbot) เป็นระบบโต้ตอบข้อความอัตโนมัติที่ช่วยให้การบริการตนเองสามารถทำได้ง่ายขึ้น อีกทั้งยังสามารถช่วยจัดการกับคำถามที่ซับซ้อน พร้อมตอบคำถามได้ตลอด 24 ชั่วโมง แชทบอ�能มาถูกนำมาใช้ในภาคการศึกษาในหลาย ๆ ส่วน ในหลายมหาวิทยาลัยได้นำแชทบอทมาช่วยในการให้ข้อมูลและตอบคำถามที่เกี่ยวกับการเข้ารับศึกษา ในงานวิจัยนี้ได้มีการใช้แพลตฟอร์ม Facebook (Facebook) ของสาขาวิชานี้เป็นตัวอย่างเพื่อแสดงให้เห็นถึงประโยชน์ของการนำแชทบอทมาใช้ และเพื่อแสดงให้เห็นกระบวนการพัฒนาแชทบอท โดยใช้ Google Dialogflow เป็นแพลตฟอร์ม NLU และใช้ Facebook Messenger เป็นส่วนติดต่อผู้ใช้ โดยผู้วิจัยได้มีการรวบรวมประโยคต่อท้ายจากประวัติการสนทนาทั้งหมด 807 ประโยค จากผู้ใช้ 125 คน ซึ่งสามารถจัดกลุ่มและพัฒนาเป็น 33 Intents และได้มีค่า precision, recall และ F1-score เท่ากับ 0.984, 0.884 และ 0.897 ตามลำดับ

คำสำคัญ: Artificial intelligence, Chatbot, Conversational agent, Chatbot platform, Dialogflow

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1. Introduction

In the past few years, millennials are increasingly turning away from calling for support and choosing to text (Reddy, 2017). This is because they were exposed to technology at an early age. Millennials’ texting habits are evident, as they prefer the efficiency of texting to call (Long, 2018).

Artificial intelligence has been deployed across a wide range of use cases to solve business problems. It appears that there are various benefits achieved with A.I. technologies, such as enhancing relationships with customers, lowering costs, and discovering new insights (Deloitte, 2020). All of these lead to the widespread implementation of AI-based chatbots (Adam et al., 2020). Chatbots are used across a wide range of domains for many different purposes, particularly customer service and personalization.

Chatbots have been used for educational purposes, which can be categorized into those with educational intentionality and those without. Chatbots without education intentionality are employed in administrative tasks such as student guidance and assistance (Sandu, 2020). Every year, many prospective students visit college websites or call the admission offices to inquire about the admission process, admission schedule, scholarships, and course fees. To satisfy the demands of this fast-paced generation, educational institutions should also improve their student communication processes. The speed of communication and ease of use has given a perfect spot for chatbots in the Millennials compared to traditional tools.

Chatbots are able to support higher education administrative functions from admissions to student services since chatbots can provide information quickly and effectively, in some contexts more efficiently than human agents. Furthermore, students would not have to wait for a response and would engage in real-time chats with these bots (Singh, 2018). There is evidence that many colleges are using a chatbot to answer routine questions about enrollment, such as financial aid and registration. Some institutions also employ artificial intelligence to assess applicants and respond to common enrolling questions (The Chronicle of Higher Education, 2018).

Previous studies have discussed the application of chatbots in the education sector. However, there is limited research on the development process of Thai chatbots focusing on the methodological aspects of development in higher education administrative functions. This paper discusses the end-to-end development process of an academic program chatbot using Google Dialogflow as NLU platform and Facebook Messenger as the platform interface.

2. Literature Review

2.1 Chatbot Technologies

One type of natural language processing computer system is chatbots. The increasing usage of chatbots is changing the way businesses interact with their customers. People can access content and services using natural language processing in chatbots (Khanna et al., 2015; Skjuve & Brandzaeg, 2019).

2.1.1 Natural Language Processing (NLP)

NLP is a field of artificial intelligence that enables computers to analyze and understand the human language, which can extract meaning and intent from the text in a readable, natural, and grammatically correct form (Deloitte, 2020). It is designed to help businesses uncover insights, answer questions, and make better decisions. As a result, many organizations, from small ventures to massive enterprises, adopt NLP into their business solutions (Loveys, 2020).

2.1.2 Natural Language Understanding (NLU)

NLU is a subfield in NLP that focuses on organizing the user’s instructed input. It is essential for the chatbot’s ability to understand and analyze the user’s expression. NLU is responsible for handling and converting unstructured data into a proper form that the system can easily understand. NLU uses machine learning and NLP techniques to extract the user’s intent and related entities from unstructured user’s input (Abdellatif et al., 2021). The fundamental aspects of NLU for building chatbots are as following:

1) **Intent classification.** An intent categorizes an end user’s intention for one conversation turn. Intent classification is also known as matching an intent. It takes end-user expressions and compares them to the training phrases of each intent to find the best match (Google Cloud, 2021).

2) **Entity extraction.** To correctly answers users’ queries, chatbots need to extract the relevant entities accurately. Entity extraction is a process of finding and classifying named entities existing in the user expressions into pre-defined categories (Raj, 2019).
2.2 Chatbot Components

The components of a chatbot are outlined in the following diagram.

**Figure 1** The basic flow for intent matching and responding to the end-user

2.2.1 Utterances
Utterances are examples of phrases received as inputs from which the chatbot needs to derive intents and entities. To train any chatbot to extract intents and entities accurately, it is imperative to capture a variety of different example utterances for every intent.

2.2.2 Intents
Intents represent a mapping between what the user says and what action should be taken. A chatbot can have as many intents as required depending on the level of conversational detail a user wants the bot to have (Google Cloud, 2021).

2.2.3 Training phrases
Because different people talk differently, the training phrases were used to provide various examples of user requests. These phrases are the real questions that help train a specific model for each use case (Google Cloud, 2021).

2.2.4 Entities
An entity is an object of interest in the chatbot’s conversations with users, which can be organized in terms of parameter names and values. The entities that the developer creates are called developer entities. In addition to developer entities, there are also pre-defined system entities. These have been designed to capture entities that are common to most domains and conversation tasks, such as dates, personal names, country names, and email addresses (Janarthanam, 2017).

2.2.5 Contexts
Contexts are designed for passing on information from previous conversations or external sources, such as user profiles. They can also be used to manage conversation flow (Google Cloud, 2021).

2.2.6 Response
Agents typically use a combination of static and dynamic responses. The primary response type is a text response. In addition to text responses, rich message types such as cards and carousels are also available depending on the integrated channels. In cases where it needs to take some action or build a more dynamic response, the agent can provide a more dynamic response by using the API or fulfillment (Google Cloud, 2021).

2.2.7 Confidence Score
When the chatbot receives the user expressions, an NLU scores potential matches with an intent detection confidence, also known as the confidence score, ranging from 0 (completely uncertain) to 1 (completely certain). If the highest-scoring intent has a confidence score greater than or equal to the classification threshold, it is returned as a match. However, if no intents meet the threshold, a fallback intent is matched (Google Cloud, 2021).

2.3 Chatbot Platforms
Because developing an NLU from scratch is complicated due to the need for NLP expertise, chatbot developers widely use NLU chatbot platforms which allow them to reduce the setup required to develop complex conversation architectures (Abdellatif et al., 2021; Munoz et al., 2018; Toxtli et al., 2018). Furthermore, previous research suggested that the application of pre-trained language models for the NLU model has shown better results than the training model from scratch. There exist several widely used chatbot platforms that are easily integrated with communication platforms. The following chatbot platforms with NLUs are popular and widely used by researchers and practitioners (Toxtli et al., 2018).
2.3.1 Dialogflow

Google Dialogflow provides human-computer interaction technology based on NLU, which can be used to build a chatbot agent with machine learning capabilities. NLU in Dialogflow is performed through the identification and matching of intent and entities. Moreover, Dialogflow supports more than 30 languages and is now supported with Google’s technology of machine learning, which makes chatbots created with it quite powerful in understanding what people say. This interface may be integrated into web and mobile apps, devices, bots, or even interactive voice response systems, such as Google Assistant. However, Dialogflow doesn’t support bot-to-human handoff or provide any web interface to achieve this.

Dialogflow uses two algorithms to match intents which are rule-based grammar matching and ML matching. Dialogflow simultaneously attempts both algorithms and chooses the best result. Rule-based grammar matching is accurate with a small or large number of training phrase examples. However, ML matching is more accurate with a large number of training phrase examples (Google Cloud, 2021).

2.3.2 Chatfuel

Similar to Dialogflow, Chatfuel is one of the leading no-code platforms for building Messenger and Instagram chatbots. Chatfuel’s greatest strength is its visual builder, which is intuitive, allowing non-tech people to design and develop automated conversational flows without compromising advanced custom coding (Chatfuel, n.d.).

2.3.3 IBM Watson Assistant

IBM Watson Assistant is one of the central AI-powered systems with prebuilt models for different domains and a visual dialog editor to simplify building the dialog by non-programmers. This platform uses machine learning to uncover common topics in existing chatlogs to quickly train your assistant on the most frequent issues and questions. However, IBM Watson Assistant doesn’t support conversational skills in the Thai language (IBM, 2021).

Table 1 Features comparison of three chatbot platforms.

<table>
<thead>
<tr>
<th>Features</th>
<th>Google Dialogflow ES</th>
<th>Chatfuel</th>
<th>IBM Watson Assistant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year launched</td>
<td>2010</td>
<td>2015</td>
<td>2007</td>
</tr>
<tr>
<td>Multilingual support</td>
<td>30+ languages (support Thai language)</td>
<td>40+ languages (support Thai language)</td>
<td>10+ languages (not support Thai language)</td>
</tr>
<tr>
<td>Omni-channel integration</td>
<td>Facebook Messenger, LINE, Twitter, Slack, etc.</td>
<td>Facebook Messenger, Instagram</td>
<td>Facebook Messenger, Slack, Webchat, Customer service desk</td>
</tr>
<tr>
<td>NLP capabilities</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Analytics</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Flow builder</td>
<td>Form-based bot builder</td>
<td>Visual conversation builder</td>
<td>Visual conversation builder</td>
</tr>
<tr>
<td>Pricing</td>
<td>Free plan: limited to 180 requests/min. Paid plan: $0.002/request</td>
<td>Free plan: limited to 50 users/monthly Paid plan: starting at USD50/month</td>
<td>Free plan: limited to 1,000 users/month Paid plan: starting at USD140/month</td>
</tr>
</tbody>
</table>

2.4 Chatbot Development Lifecycle

The chatbot development lifecycle (Sheth, 2016) contains several stages as follows:

![Chatbot Development Lifecycle](image-url)
1) **Requirements.** The goal is to understand the business process that they want to streamline with a new chatbot.

2) **Specification.** The chatbot scope will be defined in this stage. Capabilities of what the chatbot can do were also listed.

3) **Script.** Scripting is a unique step in the lifecycle compared to traditional software development, as chatbots have a conversational interface. Instead of building wireframes, the focus needs to be placed on building conversational scripts. The chatbot scripts are developed using the knowledge base, then passed back to the domain expert for validation and refinement (Cameron et al., 2018). In addition, the chatbot is given a personality to improve the user experience. The dialogue should be consistent with this personality.

4) **Architect.** The front-end and the back-end components are defined before development. The front-end is the conversational interface, and the back-end refers to web services and integrations.

5) **Development.** The development phase is when the chatbot is being developed and integrated with the communication channel.

6) **Test.** Some of the most popular and appropriate ways to assess a chatbot’s performance are user satisfaction and feedback analysis. However, it might be challenging to obtain sufficient user satisfaction or feedback data. Another technique is the algorithm inspection technique. It works by analyzing the inner working of the chatbot and ensuring that each algorithm is functioning as expected. This helps developers assess the performance of the chatbot and identify precisely where faults lie and where adjustments are required. The most common and appropriate testing procedure for these algorithms is cross-validation. This essentially uses a dataset split into training and test sets to assess how effectively an algorithm has learned to correctly perform its function (V. et al., 2020).

7) **Deployment.** Once the bot is tested, the bot must be deployed through a hosted environment.

8) **Monitor.** The chatbot was monitored for any issues or any handled queries or intents. The chatbot will be trained with further data, and more features will be added based on the user’s expectations.

9) **Promote.** Getting a stakeholder engaged helped to ensure that the chatbot gets adopted.

10) **Analyze.** The goal during this phase is to review conversation logs, review usage metrics, document false positives, and understanding missed intents to improve the chatbot for a better user experience continuously.

### 2.5 Chatbot Evaluation

The most common research methods include surveys, experiments, and usability tests. Previous research proposed the stage of usability testing before deploying the chatbot. In case of the chatbot fails to understand a user’s request, reiterating what the chatbot can do can be a helpful way of getting the conversation back on track (Cameron et al., 2018). Different techniques of usability tests were used depends on the specific conditions. Each has its own characteristics and is not able to fully meet all requirements (Ren et al., 2019).

#### 2.5.1 Dialogue system evaluation

Several metrics are used to evaluates the dialogue systems. The following are some commonly used metrics (McTear, 2021).

1) Task success
2) Task duration
3) Time-to-task is the amount of time to start engaging in a task after any instructions and other messages provided by the bot.
4) Containment rate or self-service rate corresponds to the number of users who were able to obtain the help they needed through responses given, without any helps from live agents.

#### 2.5.2 NLU components evaluation

The output of NLU is the user’s intent and the entities extracted from that intent. Thus, the evaluation of the NLU component involves comparing the component’s output with a reference representation. The test results of the intent classification can be visualized through a confusion matrix, as illustrated in Figure 3. These values can then be used to calculate the following metrics, which were often used to track and analyze in order to evaluate the performance of the NLU components (Abdellatif et al., 2021; Queudot et al., 2020):

1) **Precision** is the number of reference items correctly detected divided by the number of items detected (i.e., Precision = T.P. / (TP+FP))

2) **Recall** is the number of reference items correctly detected divided by the number of total reference items (i.e., Recall = T.P. / (TP+FN))

3) **F1-Score** is the overall measure of a model’s accuracy which is a harmonic mean of precision and recall (i.e., F1-Score = \(2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\))
2.6 Related Studies of Chatbot in Education Sectors
The use of chatbots in the education sector, both for academic and non-academic purposes, will play a prominent role in the upcoming years. Related studies of chatbots in education sectors are listed in Table 2.

Table 2 List of related studies of chatbot

<table>
<thead>
<tr>
<th>Intention</th>
<th>Title</th>
<th>Focus</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic</td>
<td>The Challenges of Using Arabic Chatbot in Saudi Universities</td>
<td>Language-rated challenges and obstacles for implementing an effective chatbot for academic uses</td>
<td>Almurayh, 2021</td>
</tr>
<tr>
<td></td>
<td>Development of an AI Userbot for Engineering Design Education Using an Intent and Flow Combined Framework</td>
<td>Chatbot development for education purposes using Google Dialogflow, evaluated by semi-structured interviews</td>
<td>Chien &amp; Yao, 2020</td>
</tr>
<tr>
<td></td>
<td>Artificial Intelligence (A.I.) Chatbot as Language Learning Medium: An inquiry</td>
<td>Types of chatbots and the possibility of their use as a language learning medium</td>
<td>Haristiani, 2019</td>
</tr>
<tr>
<td></td>
<td>A Prototype of Google Dialog Flow for School Teachers’ Uses in Conducting Classroom Research</td>
<td>Chatbot development for education purposes using Google Dialogflow, evaluated by teacher performance</td>
<td>Sajjananroj et al., 2020</td>
</tr>
<tr>
<td></td>
<td>Adoption of AI-Chatbots to Enhance Student Learning Experience in Higher Education in India</td>
<td>Factors affecting the adoption of chatbots to enhance the student learning experience</td>
<td>Sandu, 2020</td>
</tr>
<tr>
<td>Non-Academic</td>
<td>Development of Chatbot Application for Student Service Case Study: Division of Student Development Rajamangala University of Technology Suvarnabhumi</td>
<td>Chatbot development for student services, evaluated by I.T. expert, user satisfaction</td>
<td>Budsabok et al., 2020</td>
</tr>
<tr>
<td></td>
<td>Educational Response and Notification System using LINE Bot</td>
<td>Chatbot development using Google Dialogflow, evaluated by user satisfaction</td>
<td>Chaipram et al., 2020</td>
</tr>
<tr>
<td></td>
<td>A.I. Based Student Bot for Academic Information System using Machine Learning</td>
<td>Chatbot development for current student services using Node.js and AngularJS, evaluated by validated based on the quality of response, and it performed well</td>
<td>R et al., 2019</td>
</tr>
<tr>
<td></td>
<td>Messenger’s Chatbot Based on Artificial Intelligence for Digital Library Service</td>
<td>Chatbot development for digital library service using Node.js and AngularJS, evaluated with K-Fold cross-validation</td>
<td>Sangkrajang &amp; Tangwannawit, 2020</td>
</tr>
</tbody>
</table>

3. Methodology
Although there were several ways of chatbot development, this study focuses on the methodological aspects of development in higher education which may leave out or combine the various phases of the chatbot development lifecycle (Cameron et al., 2018). The following are the steps we follow while developing chatbots.

3.1 Requirement and specification
The first phase of the chatbot development process will help us understand requirements in detail, including understanding what problem the chatbots are going to solve, what goals the chatbots want to achieve, and who the target audience is.

This study chose one of the academic program Facebook Page in Thailand since the implementation of chatbots can solve its problems. The Facebook page was used as a primary means to make administrative announcements and distribute important messages to prospective students and other interested members. At present, page admins manually respond to users’ queries by giving the answer in the chat window, guiding them to the school website, and asking the user to call the school office.
3.1.1 Business problems.

1) Repetitive work.
   According to chat logs, page admin tends to provide answers to repetitive questions like admission schedule (15.0%), short courses (9.3%), academic programs information (9.3%), and problems using the online admission system (7.2%).

2) High response time.
   The amount of time it takes page admin to respond to a message is approximately 8 hrs 45 mins. The number is an average response time to messages received in April 2021.

3) Outside office hours contact.
   The proportion of messaging during off-hours (9 AM – 5 PM) that admin and users interact with the chat channel is 37.5% and 34.2%, respectively.

4) Information Limitations
   In order to provide more detailed information to the end-user questions, a certain level of information needs to be prepared. Since most of the information is on the school website, almost half of the total sessions that page admins manually guide each user to the school website (31.3%) and contact the school office via phone (24.8%) for further information.

3.1.2 Purposes of chatbot.

1) To enable the self-service solution.
2) To provide instant responses.
3) To lowering call volume by providing answers to the common questions

3.1.3 Stakeholders.
   The stakeholders include GSAS staff and faculty members who provide an answer via Facebook Messenger.

3.1.4 Target audience.
   The target audience of this Facebook page is prospective students.

3.2 Script

Research shows that personality is a key driver of chatbot engagement and repeat use. Creating a chatbot persona helps to generate trust (Campana, 2020). In terms of expertise level, users perceive an answer of a specialist as more credible than a generalist’s one. Thus, it is generally recommended that chatbots offer different characters for different topics, and chatbots should communicate like experts. Therefore, the natural language output of chatbots should be formulated professionally and expertly with human traits (Zumstein & Hundertmark, 2017). Gender stereotypes are also described in psychology and sociology literature. There are specific contexts in which a no gendered bot is more appropriate or effective (Katz, 2019).

At this stage of the chatbot development, we also designed a chatbot conversation flow that determines how the user interacts with the bot. The information that was developed to be the response of intents was gathered from the institute website, school website, and official admission announcement. A total of 807 sentences from 125 users were collected from the chat logs as a representative sample. After removing phrases with no specific intents, only 670 sentences were left manually labeled and organized into 33 intents, as shown in Figure 4.

Figure 4 Top 20 frequently mentioned intents
3.2.1 Welcome Intent
When the user begins a conversation with the agent, welcome text and a series of quick reply buttons were displayed to help the user reach the correct answer and avoid confusing the chatbot through open questions. This technique allows the chatbot and the user to be engaged in an effective dialogue (Almurayh, 2021). The menu options were selected based on the volume of the receiving messages from the chatlogs. Moreover, this menu guidance is sufficient for answering top FAQs that makeup ~40% of support queries.

3.2.2 Fallback Intent
Fallback intents are triggered if a user’s input is not matched by any of the intents. If the agent still cannot understand the user’s input within two tries, the chatbot would recommend user contact the administrative office.

![Image](image_url)

**Figure 5** The visual flow of the conversation

3.3 Architect and develop
Dialogflow was selected based on different criteria, including pricing, languages supported, and channels on which the chatbot needs to be integrated. In addition to this, previous research also suggested that Dialogflow is outperforming other NLUs in intents classification and entity extraction (Abdellatif et al., 2021).

After the conversation flow is defined based on requirements, the chatbot agent was built with Google Dialogflow. All components of the chatbot were developed at this stage.

3.4 Test
Chatbots must be properly tested to ensure that they do not fail under any circumstances. Algorithm testing is a potential solution to these problems, even though there are many methods to test chatbots. K-Fold cross-validation is one of the popular cross-validation techniques in which the model is trained on the training set and is iteratively tested on the test set for k time. For this reason, every data point has been used as testing data. (V. et al., 2020). The advantages of the K-Fold cross-validation include the ability to identify which topics the chatbot will have more trouble figuring out the user’s true intent (Consciencia et al., 2018). In addition to this, this technique helps to generate the test data itself in the early stage of the model building when the test data is limited (Alvarez, 2021).

Before randomly splitting these utterances into train and test sets, any misclassified and duplicates phrases were removed and would not be used in K-Fold cross-validation to avoid the risk of producing an inaccurate response. Therefore, only 440 sentences were split into five folds (K = 5), then one-fold was used at a time as the testing fold and the rest of the data as the training data. The process was then repeated five iterations. Afterward, the overall accuracy was estimated by averaging the accuracy values produced by all five folds.

3.5 Deployment
Once the development and testing were completed, the final model was retrained on the whole data. Dialogflow was integrated with Facebook Messenger so that the users on the Facebook platform can also use it. The Dialogflow integration sends messages to the end-user by using the Facebook Messenger API and receives messages from the end-user by acting as the Facebook Messenger Webhook.
3.6 Monitor
Once the chatbot gains users, monitoring conversational logs can allow the developer to pinpoint any other conversation breaks that are not discovered at the testing step. After analyzing the conversational logs, the scripts can be refined, and any dropped conversation points addressed, repeating steps in the lifecycle to improve the chatbot continuously.

The training tool in Google Dialogflow is used to review conversations the chatbot agent has had with end-users and to improve training data. This allows the developer to review actual conversations and the intents that were matched for each conversational turn.

4. Results and discussion

4.1 Results
The evaluation metrics results under 5-fold cross-validation are shown in Table 3. To improve the precision of an intent classification, the training data must be reviewed to ensure consistent mapping of utterances to that intent. In addition, to improve recall of an intent classification, more training utterances need to be added to the agent.

Table 3 5-Fold cross-validation results

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.989</td>
<td>0.967</td>
<td>0.977</td>
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<tr>
<td>2</td>
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<td>0.883</td>
<td>0.897</td>
</tr>
</tbody>
</table>

4.2 Discussion
The implementation of a chatbot over the Facebook Page could help the school and page admin solve their issues which can be summarized below.

1) **Increasing operational efficiency.** The chatbot allows page admin to spend more time on complex tasks instead of providing answers to basic questions. It is able to automatically guide the user to information sources that are more accurate than manually providing each user an answer.

2) **Shorten response time.** The chatbot can instantly reply to users simultaneously. Moreover, message replies that Facebook Messenger sends manually and via Dialogflow are included in the calculation of Page’s response rate and time which will be displayed publicly to visitors on “About” section of the Facebook Page.

3) **Providing 24/7 support.** Chatbot helps page admin to respond to the users’ requests, especially outside office hours.

5. Conclusions
This paper has discussed the development process of higher education chatbot, focusing on the administrative function for an academic program Facebook Page in Thailand. The chatbot agent was built using Google Dialogflow, which has made it easier to build functional and fully customize chatbots. As mentioned in the methodology section, we separated the chatbot development process into six stages.

1) **Requirement and specification.** The business problems, purposes of chatbot, stakeholders, and target audience were defined.

2) **Script.** The utterances collected from the chat logs can be classified into 38 intents. The response for each intent was gathered and developed from the information sources, such as the school website, institute website, and official announcement.

3) **Architect and development.** Google Dialogflow was selected based on its features and capabilities.

4) **Test.** The chatbot was evaluated using K-Fold cross-validation. The precision, recall, and F1-score reported as 0.984, 0.883, and 0.897, respectively.

5) **Deployment.** The chatbot agent was integrated into Facebook Messenger.

6) **Monitor.** The implementation of the chatbot allows the institution to utilize this data to track the user’s queries and identify the areas where the chatbot needs to improve.
6. Limitations and Future Research

6.1 Limitations
Although the objective of this study was accomplished, some limitations should be noted.

1) The number of user utterances that could be used as training phrases is limited since it is unable to export chat history from Facebook directly.
2) Users may send long messages that are too complex. For this reason, the chatbot agent should be designed to hand off the conversation to a human agent. However, Google Dialogflow ES doesn’t support bot-to-human handoff.
3) Due to limited time, there are not enough utterances to test the NLU components at the monitor phases.

6.2 Future Research
Three aspects that can be considered in future studies are as follows:

1) **Providing a more dynamic response.**
   This chatbot agent now uses only static responses. Using fulfillment for an intent allows users to type in questions and get an answer without navigating away from their chat window.

2) **Increasing intent coverage**
   A more significant number of intents could widen coverage on user queries which could help to provide an in-depth detailed response to different users’ questions. Expanding intent coverage is performed by manually examining utterances from the chatlogs, looking for patterns that existing intents are not covering.

3) **Increasing dataset size.**
   A chatbot with little training is bound to deliver a poor conversational experience. For a chatbot to deliver a good conversational experience, it is recommended that the developer need to add different variations of training phrases of each intent.

4) **Assessing the quality of training phrases.**
   In order to avoid confusing the agent with phrases irrelevant to the intents, the quality of training phrases supplied to the intents should be analyzed and evaluated. To improve the quality of the training phrases for your intents, the phrases in different intents with high similarity should be changed or removed.

7. Reference


Alvarez, B. (2021, January 4). *How to stop your chatbot giving the wrong answers.* https://chatbotsjournal.com/how-to-stop-your-chatbot-giving-the-wrong-answers-50ffcd7a22e9


